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Foreword

This special issue of *Theoretical Computer Science* is dedicated to the Ninth International Conference on Algorithmic Learning Theory (ALT'98) held at the European education centre Europäisches Bildungszentrum (ebz) Otzenhausen, Germany, October 8–10, 1998. It contains seven articles that were among the best in the conference. The authors of these papers have been invited by the Guest Editors to submit completed versions of their work for this Special Issue. Once received these papers underwent the usual refereeing process of *Theoretical Computer Science*.

The series of workshops on Algorithmic Learning Theory was established in 1990 in Tokyo. Since then, it has been held annually sponsored by the Japanese Society for Artificial Intelligence. The 1991, 1992, and 1993 meetings were held in Tokyo. In 1994, ALT went abroad for the first time when it was held at Reinhardsbrunn Castle in Germany. On that occasion, it merged with the International Workshop on Analogical and Inductive Inference. Subsequent meetings took place in Fukuoka (1995), Sydney (1996), and Sendai (1997).

The ALT series is focusing on all areas related to algorithmic learning theory. The diversity of approaches to learning is also reflected in this Special Issue.

The problem of learning logic programs has been widely studied within the ALT series. In the present issue, Krishna Rao and Sattar present a polynomial-time learning algorithm for a rich class of logic programs. The information source are equivalence, subsumption and request-for-hint queries. Input to a subsumption query is a clause C, and it is answered "yes" iff C is a tautology or $H^* \models C$, where H^* denotes the target concept. Otherwise, the answer is just "no." A request-for-hint query takes as input a ground clause, and answers "yes" provided C is subsumed by H^*. Otherwise, the reply is "no" and a hint, i.e., an atom along with a suitable substitution that can be refuted from target and the body of ground clause is returned. As a matter of fact, all these queries can be answered in time polynomial in the length of the target and C. The main new feature included in their article is the target class of finely moded logic programs that allow to include *local variables*. Moreover, background knowledge previously learned is incrementally used during the learning process.

The next paper also deals with learning via queries. Fischlin asks whether or not learning from membership queries can be speeded up by parallelizing it. Defining the depth of a query q to be the number of other queries on which q depends upon and the query depth of a learning algorithm to be the maximum query depth taken over all queries made, the problem of whether or not a query learner can be parallelized is then equivalent to asking whether or not the query depth can be reduced. Assuming

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the existence of cryptographic one-way functions, Fischlin proves the following strong result: for any fixed polynomial d, there is a concept class $\mathscr{C}_n$ that is efficiently query learnable from membership queries alone in query depth $d(n)+1$, but $\mathscr{C}_n$ cannot be weakly predicted from membership and equivalence queries in depth $d(n)$.

Inductive inference is another core area of the ALT meetings. Thus, this area is also well reflected within the current special issue. There are both fairly new approaches and more traditional ones to study fundamental questions of learning within the setting of inductive inference.

Stephan and Ventsov address the problem whether or not background knowledge may help in learning (here called as semantical knowledge). They consider language classes defined via algebraic structures (e.g., monoids, ideals of a given ring, vector spaces) and the background knowledge is provided in the form of programs for the underlying algebraic operations. What is shown is that such background knowledge can improve both, the overall learning power as well as the efficiency of learners (measured by the number of mind changes to be performed). Surprisingly, a pure algebraic notion is characterized in terms of pure learning theory. A recursive ring is Noetherian iff the class of its ideals is behaviorally correct learnable from positive data.

But there are more ways to attack the problem of how additional knowledge may help. In her ALT'95 paper, Meyer has observed that in the setting of learning indexed families from positive data, probabilistic learning under monotonicity constraints is more powerful than deterministic learning. A probabilistic learner is allowed to flip a coin each time it reads a new example, and to branch its computation in dependence on the outcome of the coin flip. The monotonicity constraints formalize different versions of how to realize the subset principle to avoid overgeneralization, and these formalizations go in part back to Jantke's paper at the very first ALT meeting in 1990. In her present paper (comprising her COLT'98 and ALT'98 articles), Meyer asks what knowledge is necessary to *compensate* the additional power of probabilistic learners. Now, knowledge is provided in form of oracles, and instead of flipping a coin, the deterministic learner may ask the oracle A a membership query, i.e., "$x \in A$?," where x depends on the examples received so far. To get a flavor of the results obtained, we just mention the following. For every oracle A which is Turing reducible to the halting problem, there exists an indexed family which is properly conservatively identifiable with probability $\frac{1}{2}$ and, moreover, this family exactly reflects the Turing degree of A.

A natural variation of learning is prediction. Case et al. consider this problem for target classes of functions. The new aspect studied is that the targets may *drift* over time. While similar questions have been addressed within other learning models, this is the first paper where studies concept drift in a more general computability setting. Different versions are proposed and related to one another. Moreover, the authors also analyze the learnability of some natural concept classes within their models. This is a nice combination of abstract and concrete examples.

Another extension of the classical model of inferring recursive functions is presented by Hirowatari and Arikawa. They look at the problem of learning recursive *real-valued* functions. These functions are regarded as computable interval mappings. Both coincidences and surprising differences to the learnability of recursive natural-valued functions are shown. In particular, these differences are established with respect to recursively enumerable classes and consistent identification. This work considerably extends their results presented at ALT'97.

Last but not the least, Apsītis et al. shed considerable light at a very old problem. Suppose you have a learner for a class U_1 and another learner for a class U_2. Now, it would be nice to have a more powerful learner that can identify simultaneously U_1 and U_2. However, learning in the limit is not closed under union. Thus, the authors studied the following refined version of closedness under union. Assume you have classes $U_1,\ldots,U_n$ each of which is learnable in the limit. What can be said about the learnability of the union of all these classes provided that every union of at most $n-1$ classes is learnable in the limit? Clearly, the answer may depend on n, since for $n=2$ the answer is *no* as mentioned above. Therefore, more precisely, one has to ask whether or not there exists an n such that the union of all such classes is always learnable. The minimal such n is referred to as the closedness degree, and the authors determine this degree for a large number of learning types.

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